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MANAGERIAL MONITORING OF A SINGLE DATA STREAM

by

Michael E. Treacy

WP 1210-81 April, 1981

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INTRODUCTION

Much of management activity involves monitoring: scanning and surveying situations for which there is a potential need for corrective action. The purpose of monitoring is to routinely assess this potential and thereby to indicate when managerial intervention is required. If there is never a need for corrective action, then there is never an economic benefit to monitoring, for payoffs are obtained only through actions which improve the economic circumstances of the firm.

Monitoring involves the gathering and assessment of information. It is what Simon calls the intelligence phase of decision making[1977] and what Pounds calls the process of problem finding.[1969] Monitoring is differentiated from other managerial information processing activities by its purpose, to routinely assess the potential need for corrective action. Routine implies a repetitive and somewhat structured activity. Corrective action suggests that the situation is being guided toward some target or goal.

This paper is an inquiry into the design of information systems to support managerial monitoring functions. The guiding paradigm in this effort is provided by information economics theory. As Treacy[1981] has observed, economics models of information value concentrate upon only the choice phase of decision making. Yet, we know that decisions are profoundly affected by information at the intelligence and design phases of the decision making process, because without information to

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identify problems, structure alternatives, and estimate consequences, no choice from among alternatives is ever made. Therefore, this present effort will also serve to extend information theory into the first phase of decision making, intelligence.

Our primary concern is with the design of information systems, not their valuation, yet we can hardly begin to separate good from bad design without some rudimentary ability to assign relative values. These values must be relevant in the context in which information support system design is contemplated. Therefore, any information system valuation model must be founded upon a realistic description of the managerial use of information in monitoring, even if that description is at odds with prescriptive theory.

The next section of this paper outlines a general framework for describing the monitoring function of management. Monitoring is characterized as a decision of whether or not to intervene in a situation. The decision is made by comparing the subjective probability that the situation is in need of intervention, determined from the monitored data and personal judgement, with a threshold probability determined from the relative costs and benefits of intervening. In subsequent sections, normative cost investigation models, which prescribe the determination of the subjective probability and the threshold probability, are reviewed with an aim toward selecting from them that which is descriptive of managerial monitoring behavior. Unfortunately, not all of the theory is descriptively valid. This the researchers readily admit when they bemoan the minimal

acceptance of their work by managers.[Kaplan 1975; Magee 1976]

We shall next move to Pounds work on the process of problem finding, which provides a description of how managers subjectively evaluate the probable need for intervention. A mathematical version of this description is developed to complete a descriptive model of managerial monitoring behavior. Based upon this description, a model of the value of an information support system is derived. This model indicates a need to reconsider the standard concept of an information system as simply a collection of information signals.

The developments in this paper are limited to a consideration of managerial monitoring of one situation. We shall not consider the issues of monitoring multiple data streams or of the distribution of management attention among several situations and how this affects the design of information support systems. For one approach to this latter problem see Rockart[1979].

THE GENERAL FRAMEWORK

Monitoring is performed to assess the need for managerial intervention. It may conveniently be modelled as a process in which a manager views data for the purpose of choosing whether or not to intervene into a situation. This is compatible with Simon's characterization of the intelligence phase of decision making as finding an occasion for making a decision before possible courses of action have been considered.[Simon 1977, p. 40] It is decision making with minimal

structure.

Let us assume that a situation is being monitored using a single stream of reported data, one datum arriving in each time period and each denoted by y. Also let us assume that the situation always exists in one of two states, in control (s_0) or out of control (s_1). In each time period, the manager has two possible actions open to him. He can intervene (a_1) or not intervene (a_0). For each state-action pair there is associated a payoff u. These payoffs are shown in Figure 1.

	s_0 in control	s_1 out of control
a_0: don't investigate	$u(s_0,a_0)$	$u(s_1,a_0)$
a_1: investigate	$u(s_0,a_1)$	$u(s_1,a_1)$

Figure 1

By definition, we have that:

$$u(s_0,a_0) > u(s_0,a_1) \quad (1)$$

$$\text{and } u(s_1,a_0) < u(s_1,a_1) \quad (2)$$

That is, in the out of control state it is better to intervene and in the in control state it is better not to intervene. The manager will want to intervene in the situation if the expected payoff of intervention exceeds the expected benefits of nonintervention. If we let $p(s_1)$ represent the manager's subjective probability that the situation is out of control, then he should intervene, choose action a_1, if:

$$[1 - p(s_1)].u(s_0,a_1) + p(s_1).u(s_1,a_1) > [1 - p(s_1)].u(s_0,a_0) + p(s_1).u(s_1,a_0) \quad (3)$$

$$\Rightarrow \quad p(s_1) > \frac{[u(s_0,a_0) - u(s_0,a_1)]}{[u(s_0,a_0) - u(s_0,a_1)] + [u(s_1,a_1) - u(s_1,a_0)]} = p^T \quad (4)$$

p^T represents a threshold probability. If the subjective probability of being out of control exceeds this threshold, then the manager will want to act. Data is observed to determine $p(s_1)$, the probability of the situation being out of control.

Notice that the general framework has made two restrictive assumptions, that the situation can assume only one of two states and that the manager monitors only one stream of data. We shall argue that this first assumption is sufficient for an initial descriptive theory of managerial monitoring behavior. The simplification is made to reduce both the complexity and the information requirements of the model as a parallel to simplifications made by managers to reduce information processing requirements. The second assumption shall be relaxed in a subsequent paper. The limit of two actions is not a restriction, but by definition of the intelligence activity as the earliest phase of decision making, before the problem has more than minimal structure. The rest of the notation, including the derivation of the intervention rule is just that, notation. It provides no restriction upon possible managerial behavior other than consistency.

DETERMINATION OF THE THRESHOLD PROBABILITY FOR INTERVENTION

How does a manager determine p^T, the threshold probability of the situation needing intervention? One approach is to directly estimate the four payoffs, u, and to compute p^T from equation (4). This appears to be an unlikely description of managerial behavior.

Dyckman[1969], in a paper on the prescriptive theory of cost variance investigation, suggested that the manager should subjectively determine two values: C, the cost of investigation and L, the present value of the gross savings obtained from an investigation when the situation is out of control. If the cost of investigation is independent of the state, then these values correspond to payoffs as follows:

$$C = u(s_0,a_0) - u(s_0,a_1) \tag{5}$$

$$L - C = u(s_1,a_1) - u(s_1,a_0) \tag{6}$$

Equation (5) reflects the benefits of choosing the correct action when the situation is in control. Equation (6) reflects those benefits when out of control. The threshold probability of intervening now takes on a simple form:

$$p^T = C/L \tag{7}$$

Dyckman concedes that "the precise determination of the savings for each future period is not an easy matter." He observes that "where a corrective action is not forever binding, the calculation of L needs to be adjusted to reflect the possibility of future out of control periods" and that "data on the average number of periods before the

process is discovered to be out of control may be helpful."[Dyckman 1969, p. 218] These are the types of tradeoffs that managers must implicitly make in their decision to intervene.

Li[1970] has criticized the theoretical validity of Dyckman's approach for setting p^T because it does not anticipate the benefits of waiting for another reported datum with which to sharpen the manager's subjective probability of being out of control, $p(s_1)$. He advocates using Kaplan's dynamic programming approach [1969], which explicitly models the sequential nature of the monitoring process and computes threshold probabilities which converge to a constant value as the number of periods increases. Dyckman responded that "the difficulties attendant on solving large and complex real dynamic programming problems can limit the succesful application of this technique." He is supported by Magee[1976], whose comparison of the approaches using simulation concluded that "Li's criticism of Dyckman's approach for not considering future actions, while valid theoretically, may have little effect on the incremental cost savings." Another comparison by Jacobs[1978] using an experimental setting, failed to indicate any significant differences between the results of using Dyckman's and Kaplan's approach.

Our interest is in using parts of these prescriptive models of cost variance investigation decisions which have descriptive validity. A dynamic programming approach would hardly appear to be a valid description of managerial behavior. Dyckman's approach, alternatively, although theoretically flawed, has a certain face validity which makes

it appealing. We shall incorporate it into our model of managerial monitoring behavior.

NORMATIVE DETERMINATION OF THE POTENTIAL NEED FOR INTERVENTION

We have assumed, to this point, that the manager uses a single stream of data to monitor a situation. The data is observed to assess the probability of need for intervention, $p(s_1)$, in any period. Under these circumstances, there can be only three influences upon the manager's determination of $p(s_1)$: his initial judgement, the stream of data, and the passage of time.

We shall present the normative approach to the determination of $p(s_1)$ as developed in the cost variance investigation literature. On this approach, there is little disagreement between Dyckman, Kaplan, and other theoreticians, although formulations do differ. Details may be found in Dyckman[1969] and Kaplan[1975]. Next we shall assess the descriptive validity of the theoretical treatment and, unfortunately, be forced to reject the approach as a description of the managerial determination of the potential need for intervention. A new approach shall be presented in a subsequent section.

Let us define $p'(s_1)$ as the probability that the situation is in need of intervention at the start of a period, before the new datum or the passage of one more time period have been considered. $p'(s_1)$ summarizes all relevant information since the last intervention: the manager's judgement of the need for intervention immediately after the

intervention and all prior observations and time since the last intervention.

The new datum, y, is prescribed to be incorporated into the probability estimate using Bayesian revision.

$$p(s_1|y) = \frac{f(y|s_1)p'(s_1)}{f(y|s_0)p'(s_0) + f(y|s_1)p'(s_1)} \qquad (8)$$

For this calculation, the manager requires knowledge of two distributions, $f(y|s_0)$ and $f(y|s_1)$. These are the conditional probabilities of the observed datum under each state.

Incorporation of the time information requires assumptions about the nature of the process underlying the situation. If the situation moves from state s_0 to state s_1 with probability g_{01} and from s_1 to s_0 with probability g_{10} during any period without intervention, then:

$$p(s_1) = p(s_0|y)g_{01} + p(s_1|y)[1 - g_{10}] \qquad (9)$$

$$= [1 - p(s_1|y)]g_{01} + p(s_1|y)[1 - g_{10}] \qquad (10)$$

If it is assumed that the situation never moves from s_1 to s_0 without intervention (g_{10} =0), then the process is one of geometric decay. The longer the situation is left unattended, the greater the probability that it is in need of intervention. In such a case:

$$p(s_1) = p(s_1|y) + [1 - p(s_1|y)]g_{01} \qquad (11)$$

$$\geq p(s_1|y) \qquad (12)$$

Geometric decay is usually assumed in the cost investigation literature, probably because much of the theory was borrowed from quality control theory, where a misadjusted machine has no self correcting ability. The same is not generally true in a management situation, where one is monitoring the outcomes of others' actions. Here the effect of time on $p(s_1)$ is ambiguous. In the general case, $p(s_1) > p(s_1|y)$, if and only if:

$$\frac{g_{01}}{g_{10}} > \frac{p(s_1|y)}{1 - p(s_1|y)} = \frac{p(s_1|y)}{p(s_0|y)} \qquad (13)$$

Since the ratio on the right varies from period to period, the effect of time may in one period be to increase $p(s_1|y)$ and in another to decrease it. Even this ambiguous result is fundamentally dependent upon assumptions about the nature of the process underlying the situation. Different assumptions lead to different theory.

DESCRIPTIVE VALIDITY OF THE NORMATIVE APPROACH

Having described normative theory for the determination of $p(s_1)$, we must assess its relevance to a description of managerial monitoring behavior. The theory considers three determinants of $p(s_1)$: prior judgement, the stream of data, and the passage of time. We shall assess these three aspects of the theory against other available evidence.

Normative theory directs that prior judgements should affect the determination of $p(s_1)$ through Bayesian revision. In that fashion:

$$\frac{p(s_1|y)}{p(s_0|y)} = \frac{f(y|s_1)}{f(y|s_0)} \cdot \frac{p'(s_1)}{p'(s_0)} \qquad (14)$$

In words, managers should form odds of being in s_1 versus s_0 equal to the product of the likelihood ratio of y and the prior odds on s_1 and s_0. There is significant evidence that in the assessment, prior odds are largely ignored. Kahneman and Tversky [1972, 1973] have produced the most compelling evidence of this systematic underutilization of prior information. Their basic conclusions are supported by Swieringa, et al[1976], who conclude that the degree to which the prior odds are ignored are directly related to the strength of association between the data stream and the situation.[p. 182]

The evidence suggests that Bayesian revision is a poor description of how managers utilize prior judgements. We posit that there is just as little support for Bayesian revision as a description of how new data are utilized. Our claim rests upon the observation that the conditional probability functions $f(y|s_0)$ and $f(y|s_1)$ are enormously difficult to generate, especially in a monitoring context.

Consider, for a moment, weather forecasts and tomorrow's weather conditions. The forecast is information; it corresponds to y. Tomorrow's weather condition (rain or sun) is the uncertain state. Now think of your favorite weather forecaster and estimate the probability that he will forecast rain given that it will be sunny tomorrow,

f(y|s). An important difficulty immediately arises. The problem is backwards to the normal fashion of thinking about information and states. The probability of sun tomorrow, given a forecast of rain, p(s|y), is a more natural assessment, because it is chronologically ordered (first an information signal, then an inference about the state) and it measures the natural notion of reliability of information. This example illustrates the inadequacy of Bayesian revision as a descriptive theory where prior judgements are not revised, but largely ignored.

Although this paper is in the information economics tradition, we must reject the Bayesian revision formulation of the manager's intervention decision, for we wish to base our information value theory upon a valid description of managerial behavior. The evidence leads us to agree with Kahneman and Tversky [1972, p. 450] when they conclude that "in his evaluation of evidence, man is apparently not a conservative Bayesian: he is not Bayesian as all." We maintain that a non-Bayesian formulation is better suited to a descriptive theory of probability assessment in the managerial monitoring context.

Finally there is the matter of the influence of time upon the assessment of the potential need for intervention. The normative theory is fundamentally dependent upon assumptions about the nature of the process underlying the situation. Different assumptions yield different theory. Any realistic assumptions, though, will yield one consistent result: the influence of the passage of time will be small compared to the influence of the data stream. For a demonstration of

this, consider equation (11), where the process is assumed to be in geometric decay. A reasonable assumption about this process is that g_{01} is quite small; the need for intervention is the exception rather than the rule. Therefore the second term on the right side of the equation is negligible in its influence upon $p(s_1)$, which is approximately equal to $p(s_1|y)$, determined from the influence of y.

In realistic managerial monitoring situations, time has some minimal influence upon the intervention decision, but only through the mechanism that distributes a manager's attention among several competing situations. We will not consider this issue in the present paper. In the assessment of a particular situation, though, time plays a negligible role. Therefore, we shall choose not to include this factor in our initial descriptive model of managerial monitoring behavior.

A DESCRIPTIVE MODEL OF THE DETERMINATION OF $p(s_1)$

We require a model of the assessment of $p(s_1)$ that utilizes prior judgements in inverse proportion to the association of observed data to the situation and that does not rely upon knowledge of $f(y|s_0)$ or $f(y|s_1)$. For guidance, we turn to Pounds' seminal work which describes the process of problem finding.[1969] Monitoring is an important class of problem finding activity.

Pounds defined a problem as a significant difference between the present condition of a situation and how it ought to be. He observed that "the manager defines differences by comparing what he perceives to the output of a model which predicts the same variables."[p. 5] A model need not be any formal piece of logic. More often than not it is simply what a manager judges ought to be. It may be derived from historical results, from plans, from a comparison of similar situations, or by mandate.

The logic of this approach is simple and clear. Pounds observed that the present condition, k, and the model or norm, n, define a difference, d, and that a manager decides whether he has a problem (state s_1) or not (state s_0) on the basis of this difference. Because the norm may be uncertain, the difference may be uncertain. Also, because the association between the data stream and the situation may not be exact, any particular difference may not indicate with certainty either s_0 or s_1. Thus, a manager's uncertainty as to whether there is a need for intervention derives from two sources: uncertainty as to how the data stream ought to be and the inadequacy of the data stream as an indicator of the present situation.

Differences are defined so that greater differences are always more indicative of a problem situation. If a larger observed value is more indicative of an in control situation, then $d = n - k$. If a smaller observed value is more indicative, then $d = k - n$. Finally, if smaller deviation from a standard in either direction is more indicative, then $d = |n - k|$. For the rest of this paper, we shall assume that the

manager is dealing with data of the second type and define $d = k - n$. Parallel results for the other two cases are left to the reader so that we may avoid unnecessary repetition. The second case has been chosen because we wish to compare our results with those of the cost variance investigation literature and cost data is of this type.

Let $f(d|y)$ represent the distribution of the manager's subjective assessment of the difference indicated by datum y and let $p(s_0|d)$ represent the manager's assessment of the probability of being in control, for a given difference d. Then:

$$p(s_0|y) = \int_{-\infty}^{\infty} p(s_0|d)f(d|y)dd \tag{15}$$

We may mathematically represent Pounds' descriptive theory of the managerial assessment of $p(s_1)$ as:

$$p(s_1) = p(s_1|y) \tag{16}$$

$$= 1 - p(s_0|y) \tag{17}$$

$$= 1 - \int_{-\infty}^{\infty} p(s_0|d)f(d|y)dd \tag{18}$$

We have chosen in equations (17) and (18) to represent $p(s_1)$ as the residual of $p(s_0|y)$. This obviates the need to clarify the nature of s_1, which may represent an amalgam of out of control possibilities.

The difference, d, equals $k - n$, the subjectively assessed difference between the present condition and the norm. The present condition is represented by the data stream, which is subject to bias and random error. Only know bias will affect a subjective assessment and we will define our data stream as already adjusted for known bias. The effect

of random error in the data stream is to make it less than perfectly reliable. We may represent the assessment of the present condition upon receipt of y, as a random variable with distribution $f_K(k|y)$. We shall operationalize $f_K(k|y)$ by assuming that it is normally distributed with mean y (the most likely condition) and variance v_K (a measure of the data unreliability).

Similarly, we may represent the manager's norm as a random variable with distribution $f_N(n)$. Since the norm is independent of the datum, $f_N(n|y) = f_N(n)$. We shall operationalize $f_N(n)$ by assuming that it is normally distributed with mean u_N (the most likely norm) and variance v_N (a measure of the manager's uncertainty). Uncertainty about the norm derives from two sources: an incomplete understanding of the relationship between the data stream and the situation and missing or unreliable data necessary for the conditional estimation of how the data stream should behave. Later in this paper, we shall explore the economic impact of an information system that facilitates a decrease in the first source of uncertainty, and hence a decrease in v_N, through managerial learning.

The difference is the sum of two normally distributed random variables, k and -n. Thus, it is also normally distributed with mean $y-u_N$ and variance $v_K + v_N$.

$$f(d|y) \sim N(y - u_N, v_K + v_N) \qquad (19)$$

Notice that all uncertainty as to the difference derives from two sources: the unreliability of the data stream and the uncertainty about the norm.

The manager's interpretation of any particular difference, represented by $p(s_0|d)$, depends upon not only the size of the difference, but also upon the association of the difference to the situation. We may represent the manager's perception of the association by r, the absolute value of the correlation between the data stream and the situation. r is a measure of the proportion of the variability in the situation that is explainable by variation in the data stream.

If there is no association whatsoever, then $r = 0$ and $p(s_0|d) = p'(s_0)$, the prior probability of being in control. If there is perfect association between the data stream and the situation ($r = 1$), then the difference is an exact indicator of the state of the situation. At some point, d_0, the difference is large enough that the manager is certain of the need for intervention (state s_1). Below d_0 the difference is too small for intervention and the manager is certain of being in control (state s_0). Then $p(s_0|d)$ is a step function of d.

$$p(s_0|d) = \begin{cases} 1 & d < d_0 \\ 0 & d > d_0 \end{cases} \qquad (20)$$

For values of r between zero and one, $p(s_0|d)$ has values between the two extremes. This is diagrammed in Figure 2.

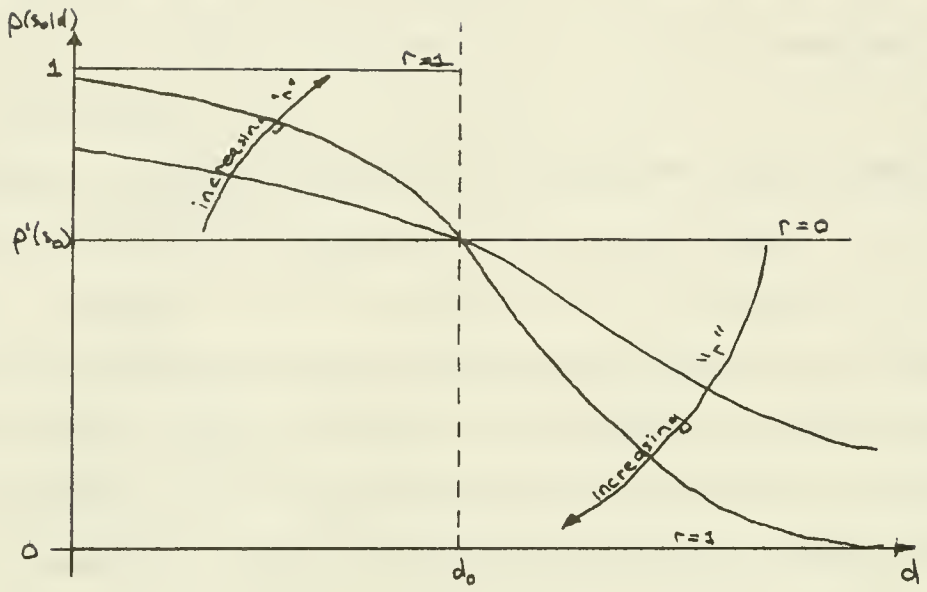

Figure 2

The difference d_0 may now be interpreted as the difference for which the manager would not change his prior judgement: $p(s_0|d_0) = p'(s_0)$. For $p'(s_0) = p'(s_1) = 1/2$, we would expect that $d_0 = 0$. If the distribution of d is symmetric about d_0, then d_0 is also the expected difference prior to the receipt of y. Later in this paper, we shall develop an explicit formulation for d_0 in terms of other primitives.

For intermediate r values, $p(s_0|d)$ as a function of d is probably not linear, but it may be approximated by a linear function, through the point $[d_0, p'(s_0)]$, as shown in Figure 3.

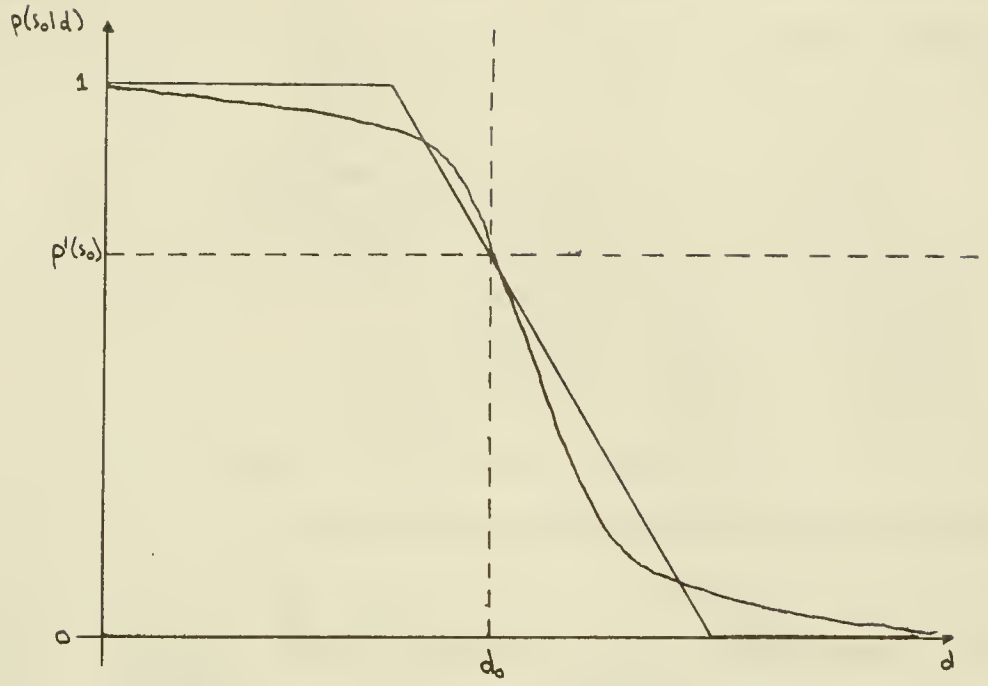

Figure 3

The slope of the intermediate section of the linear approximation depends upon r and a scale factor. A simple function for this slope, m', is:

$$m' = -\frac{A}{d_0}\cdot\frac{r}{1-r} = -m \qquad A > 0 \qquad (21)$$

A/d_0 is simply a scale factor. This function for the slope has the required property that it is monotonically negative in r and equals zero for r = 0 and negative infinity for r = 1. We have defined m as -m' so that all primitives in the subsequent equations will be positive.

The general function for $p(s_0|d)$, with m, d_0, and $p'(s_0)$ as parameters, may now be written as:

$$p(s_0|d) = \begin{cases} 1 & d < d_0 - \frac{1}{m}.(1-p'(s_0)) \\ p'(s_0) - m.(d-d_0) & d_0 - \frac{1}{m}.(1-p'(s_0)) < d < d_0 + \frac{1}{m}.p'(s_0) \\ 0 & d > d_0 + \frac{1}{m}.p'(s_0) \end{cases} \quad (22)$$

Applying equations (19) and (22) to (15) we get:

$$p(s_0|y) = p'(s_0).\left\{\Phi\left(Z + \frac{1}{\sqrt{v_K+v_N}m}.(1-p'(s_0))\right) - \Phi\left(Z - \frac{1}{\sqrt{v_K+v_N}m}.p'(s_0)\right)\right\} \quad (23)$$

$$+ 1 - \Phi\left(Z + \frac{1}{\sqrt{v_K+v_N}m}.(1-p'(s_0))\right)$$

$$-\sqrt{v_K+v_N}m.Z.\left\{\Phi\left(Z + \frac{1}{\sqrt{v_K+v_N}m}.(1-p'(s_0))\right) - \Phi\left(Z - \frac{1}{\sqrt{v_K+v_N}m}.p'(s_0)\right)\right\}$$

$$-\frac{\sqrt{v_K+v_N}m}{\sqrt{2\pi}}.\left\{EXP\left(\frac{1}{2}[Z - \frac{1}{\sqrt{v_K+v_N}m}.p'(s_0)]^2\right) - EXP\left(\frac{1}{2}[Z + \frac{1}{\sqrt{v_K+v_N}m}.(1-p'(s_0))]^2\right)\right\}$$

where: $Z = \frac{y-u_N-d_0}{\sqrt{v_K+v_N}}$, and Φ is the cumulative standard normal dis'n.

The last two terms are each approximately zero since for large r, m is very large and the right hand multiplicand is approximately zero, whereas for small r, m is small and the left hand multiplicand is approximately zero. Thus, setting these two terms to zero and applying equation (17) we arrive at an explicit formulation for a manager's assessment of the potential need for intervention.

$$p(s_1) = \Phi\left[\frac{y-u_N-d_0}{\sqrt{v_K+v_N}} + \frac{d_0}{\sqrt{v_K+v_N}}.\frac{1-r}{Ar}(1-p'(s_1))\right] \tag{24}$$

$$- p'(s_0).\left(\Phi\left[\frac{y-u_N-d_0}{\sqrt{v_K+v_N}} + \frac{d_0}{\sqrt{v_K+v_N}}.\frac{1-r}{Ar}(1-p'(s_1))\right]\right.$$

$$\left. - \Phi\left[\frac{y-u_N-d_0}{\sqrt{v_K+v_N}} - \frac{d_0}{\sqrt{v_K+v_N}}.\frac{1-r}{Ar}p'(s_1)\right]\right)$$

The logic of this formulation is hardly transparent, but we can make two further approximations that will simplify the expression for $p(s_1)$ without damaging its descriptive validity. The first term on the right side of equation (24) varies monotonically between 1 and $\Phi[(y-u_N-d_0)/\sqrt{v_K+v_N}]$ and the second term varies monotonically between $-p'(s_1)$ and 0, as r varies from zero to one. If we assume that the variation is linearly proportional to r, then we have two simplifying approximations:

$$\Phi\left[\frac{y-u_N-d_0}{\sqrt{v_K+v_N}} + \frac{d_0}{\sqrt{v_K+v_N}}.\frac{1-r}{Ar}(1-p'(s_1))\right] = \Phi\left[\frac{y-u_N-d_0}{\sqrt{v_K+v_N}}\right] + (1-r)\left(1 - \Phi\left[\frac{y-u_N-d_0}{\sqrt{v_K+v_N}}\right]\right) \tag{25}$$

and,

$$\Phi\left[\frac{y-u_N-d_0}{\sqrt{v_K+v_N}} + \frac{d_0}{\sqrt{v_K+v_N}}.\frac{1-r}{Ar}(1-p'(s_1))\right] - \Phi\left[\frac{y-u_N-d_0}{\sqrt{v_K+v_N}} - \frac{d_0}{\sqrt{v_K+v_N}}.\frac{1-r}{Ar}p'(s_1)\right] = 1-r \tag{26}$$

When equations (25) and (26) are applied to equation (24), it yields:

$$p(s_1) = r.\Phi\left[\frac{y-u_N-d_0}{\sqrt{v_K+v_N}}\right] + (1-r)(1-p'(s_0)) \tag{27}$$

$$= r.\Phi\left[\frac{y-u_N-d_0}{\sqrt{v_K+v_N}}\right] + (1-r)p'(s_1) \tag{28}$$

To interpret equation (28), note that because there is a prior probability $p'(s_1)$ that the situation is out of control, there is an expected difference, d_0, prior to the receipt of the datum. After receipt of y, the expected difference is $y-u_N$, the mean of the conditional distribution of d, which has variance v_K+v_N. Thus, $(y-u_N-d_0)/\sqrt{v_K+v_N}$ is a measure of the number of standard deviations of change in the expected difference. Note that since the expected datum value is u_N+d_0, the prior expected change is zero. $\Phi[(y-u_N-d_0)/\sqrt{v_K+v_N}]$ is a measure of the significance of the change in expected difference. It is an assessment of the potential need for intervention solely on the basis of the datum y. $p'(s_1)$ is the manager's prior assessment of the potential need for intervention and $p(s_1)$ is an average of these two assessments, weighted by the representativeness of the data stream.

From equation (28) and knowledge that $d_0 = 0$ for $p'(s_0) = p'(s_1) = 1/2$, we may derive an explicit formulation for d_0, the prior expected difference. Since we have chosen to ignore the effects of time upon the determination of $p(s_1)$, we should expect <u>a priori</u> that:

$$\text{prob}[\, p(s_1) > p'(s_1) \,] = 1/2 \tag{29}$$

$$\Rightarrow \quad \text{prob}[\, y > \sqrt{v_K+v_N}\, \Phi^{-1}(p'(s_1)) + u_N + d_0 \,] = 1/2 \tag{30}$$

$$\Rightarrow \quad 1 - F_Y[\sqrt{v_k+v_N}\, \Phi^{-1}(p'(s_1)) + u_N + d_0] = 1/2 \tag{31}$$

$$\Rightarrow \quad y^M = \sqrt{v_K+v_N}\, \Phi^{-1}(p'(s_1)) + u_N + d_0 \tag{32}$$

where F_Y is the cumulative distribution of y and y^M is the median datum value. Applying our knowledge that $d_0 = 0$ for $p'(s_0) = p'(s_1) = 1/2$ to equation (32) yields an explicit formulation of d_0.

$$d_0 = -\sqrt{v_K+v_N}\ \Phi^{-1}(p'(s_1)) \tag{33}$$

Note that this formulation does not require any knowledge of the distribution of y. Applying equation (33) to (28) yields a final formulation for $p(s_1)$.

$$p(s_1) = r.\Phi\left[\frac{y-u_N}{\sqrt{v_K+v_N}} + \Phi^{-1}(p'(s_1))\right] + (1-r).p'(s_1) \tag{34}$$

This descriptive model of a manager's assessment of $p(s_1)$ has been founded upon Pounds' descriptive theory of the process of problem finding. It overcomes the two difficulties of the Bayesian model that led us to reject that approach as descriptively invalid. First, it does not require that the manager have knowledge of $f(y|s_0)$ or $f(y|s_1)$. Second, it incorporates the theory of Kahneman and Tversky [1972, 1973] and Swieringa, et al [1976], that managers tend to ignore prior probabilities in proportion to the representativeness of the data stream.

This model has a further important advantage over the Bayesian approach. It is of the same form as the Brunswik lens model of human information processing.[Brunswik 1952, 1956] That model has received extensive attention and empirical validation, both in the laboratory and the field.[Slovic and Lichtenstein 1971] It is remarkable that our model has taken the same form, even though the development has not

relied upon Brunswikian concepts of human information processing.

THE VALUE OF THE INFORMATION SIGNAL FOR MONITORING

From equations (4), (7), and (34), we may derive an explicit decision rule for when a manager chooses to intervene into the situation. The rule is, intervene (choose a_1) if:

$$r.I\left[\frac{y-u_N}{\sqrt{v_K+v_N}} + \Phi^{-1}(p'(s_1))\right] + (1-r).p'(s_1) > C/L \qquad (35)$$

or,

$$y > \sqrt{v_K+v_N}\left[\Phi^{-1}\left[\frac{(C/L) - (1-r)p'(s_1)}{r}\right] - \Phi^{-1}[p'(s_1)]\right] + u_N + d_0 \qquad (36)$$

$$= y^T \qquad (37)$$

The a priori value of the information signal can be measured by comparing the expected value of outcomes when the signal is used minus the expected value of outcomes without the signal.[Demski 1972; Treacy 1981] It is assumed that $p'(s_1) < p^T$, that without the signal the manager was not prepared to intervene. We have:

$$V(y) = p(s_0 \text{ and choose } a_0).u(s_0,a_0) + p(s_1 \text{ and choose } a_0).u(s_1,a_0) \qquad (38)$$
$$+ p(s_0 \text{ and choose } a_1).u(s_0,a_1) + p(s_1 \text{ and choose } a_1).u(s_1,a_1)$$
$$- p'(s_0).u(s_0,a_0) - p'(s_1).u(s_1,a_0)$$

$$= p(s_0 \text{ and } y < y^T).u(s_0,a_0) + p(s_1 \text{ and } y < y^T).u(s_1,a_0) \qquad (39)$$
$$+ p(s_0 \text{ and } y > y^T).u(s_0,a_1) + p(s_1 \text{ and } y > y^T).u(s_1,a_1)$$
$$- p'(s_0).u(s_0,a_0) - p'(s_1).u(s_1,a_0)$$

Let us define $F(y|s_0)$ and $F(y|s_1)$ as the cumulative distributions of $f(y|s_0)$ and $f(y|s_1)$ respectively. These latter distributions are precisely those that we earlier argued were difficult to generate and invalid as primitives in a descriptive theory of managerial judgement. Nevertheless, they are useful and usable primitives for a prescriptive theory of information signal value. We may now write:

$$V(y) = F(y^T|s_0).p'(s_0).u(s_0,a_0) + F(y^T|s_1).p'(s_1).u(s_1,a_0) \qquad (40)$$
$$+ [1-F(y^T|s_0)].p'(s_0).u(s_0,a_1) + [1-F(y^T|s_1)].p'(s_1).u(s_1,a_1)$$
$$- p'(s_0).u(s_0,a_0) - p'(s_1).u(s_1,a_0)$$

$$= [1 - F(y^T|s_1)].p'(s_1).[u(s_1,a_1) - u(s_1,a_0)] \qquad (41)$$
$$- [1 - F(y^T|s_0)].[1 - p'(s_1)].[u(s_0,a_0) - u(s_0,a_1)]$$

Using equations (5) and (6) we may substitute for the utilities and arrive at the simple formulation:

$$V(y) = (L - C).[1 - F(y^T|s_1)].p'(s_1) - C.[1 - F(y^T|s_0)].p'(s_0) \qquad (42)$$

Unlike the information economics model, this value can be negative. A signal can lead a manager astray.

THE VALUE OF AN INFORMATION SYSTEM

In economics, the common characterization of an information system is as a collection of information signals.[Marschak 1971; Demski 1972] Thus, the value of an information system is exactly equal to the expected value of its information signals, V(y). In a recent study of sixteen executive level information systems [Rockart and Treacy 1981] it was observed that little of the value of an information system

derives from information signals about the present condition of a situation. These signals are usually available to a manager through other channels long before he sits at a computer terminal to monitor situations of interest. The information systems were valued, instead, for their assistance in sharpening a manager's norms, his "mental model" of the organization. As Ackoff[1967] earlier noted, managers rarely suffer a lack of relevant information, but an overabundance of irrelevant information. Information systems are valued not because they provide more signals, but because they allow a manager to derive more value from existing signals, through a sharpening of his norms.

Sharper norms can be achieved through two means: smaller variance v_N (more certainty) and more accurate mean u_N (more accuracy). We shall examine the effects of decreasing the variance upon V(y), the value of a signal.

Consider the first derivative of V(y) with respect to v_N. If this derivative is negative, then the value of a signal increases as the uncertainty of the norm is decreased. The value of an information signal that causes this decrease in uncertainty is equal to the gain in value of the information signal. Mathematically, we have:

$$\frac{\partial V(y)}{\partial v_N} = \frac{\partial V(y)}{\partial y^T} \cdot \frac{\partial y^T}{\partial v_N} \tag{43}$$

$$= [C.f(y^T|s_0).p'(s_0) - (L-C).f(y^T|s_1).p'(s_1)] \tag{44}$$

$$\cdot \left[\frac{1}{2\sqrt{v_K+v_N}} \cdot \left\{\Phi^{-1}\left[\frac{(C/L) - (1-r).p'(s_1)}{r}\right] - \Phi^{-1}[p'(s_1)]\right\}\right.$$

The second multiplicand of equation (44) is always positive since $p'(s_1) < p^T$. Therefore, $(\partial V(y)/\partial v_N) < 0$ if the first multiplicand is negative.

$$C.f(y^T|s_0).p'(s_0) - (L-C).f(y^T|s_1).p'(s_1) < 0 \quad (45)$$

$$(L-C).f(s_1|y^T) - C.f(s_0|y^T) > 0 \quad (46)$$

Equation (46) is satisfied as long as the threshold datum for action, y^T, of the descriptive model is greater than the Bayesian, normative threshold datum, y^B, which is defined such that:

$$(L-C).f(s_1|y^B) - C.f(s_0|y^B) = 0 \quad (47)$$

From equations (36) and (37), we note that y^T decreases as v_N decreases. Therefore, decreasing a manager's uncertainty about the norm decreases the threshold datum for action. There is a diseconomy in decreasing v_N beyond the point at which $y^T = y^B$. It is an empirical question as to whether information systems are ever capable of reducing v_N enough to produce such diseconomies.

CONCLUSIONS

We have developed a descriptive model of the managerial intervention decision using a general framework drawn from information economics. This model provides the basis for an investigation of the value of an information signal and of an information system in a monitoring context. We have explored the value of an information system that provides not unique signals on events, but assistance to a manager in sharpening his "mental model" of the data stream under observation.

Results suggest that tehre are at times diseconomies in this role.

The models of managerial behavior and of information value are far from complete. No attempt has been made to consider the monitoring of a situation with multiple signals or of a manager's difficulty in distributing his attention across different, but interrelated, situations. These matters are still under development.

Nevertheless, this work is an important first step. It provides an alternative approach to the standard normative Bayesian approach to information analysis. That approach is in need of augmentation since developments have slowed considerably under the massive weight of its overly general conceptualizations of information and decision making. Hilton[1980] provides an excellent example of the unnecessary complexity induced by the standard information economics approach. It results in models and theory which defy operationalization and, therefore, exist as untestable truisms.

The solution to these difficulties lies in specialization. The models in this paper apply to monitoring. There are no claims that they apply outside this context. Through specialization we are able to apply knowledge about the particular context, such as Pounds' work, to improve and sharpen our models. When we build upon relevant non-mathematical works, which, after all, are usually far ahead of our models, both can only gain.

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